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Intelligent Fault Diagnosis via EMD Method

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Abstract: In the first stage of failure, the vibrations of gearboxes have a low range, which are often covered with stronger vibrations of the system. Thus, diagnosing the faults of the gears of the gearbox is difficult among the vibrations of other parts of the machine. In this regard, varied mathematical methods have been used, each having its own potentials and shortcomings. Fast Fourier Transforms (FFT) and Short-Time Fourier Transform (STFT) are two of these methods. However, due to the wide range of gearbox faults, distinguishing these faults is not possible via the aforementioned methods. So, with regard to the capability of empirical model decomposition EMD method in distinguishing faults, this study investigates the gearboxes vibration signals practically and in laboratory. First some intentional faults are applied on the experimental gearboxes. Then, the group of vibration signals of varied faults is collected and the data collected from the practical test are analyzed. Finally, a neural network was offered for an intelligent fault diagnosis of the gearbox. The findings verified the suggested methods (computing standard deviation and root-mean-square) not only are accurate enough but also have reduced the size of computations to a great extent.

Key words: Fault diagnoses, EMD method, vibration signal, fast Fourier transform method

INTRODUCTION

Precise and on time diagnosis of the faults leads to a good outcome, profitable maintenance and repair methods for industrial units. This can be done by using accurate and practical scientific methods in the form of advanced machines for condition monitoring, as well as using specialists familiar to the relevant sciences and technologies. Since the mid 1950s, the measurement and analysis of the vibrations is known as the major technique in controlling the machineries' condition while working. Each mechanical fault causes vibrations with certain features. Therefore, by measuring vibrations and considering their features, we can diagnose the relevant mechanical fault. So, special sensors are used for measuring the vibrations of the machine and these measurements are recorded (Shen *et al*., 2012).

The main problem in analyzing the vibrations of the system is transforming the recorded raw signal to analyzable data for the operator. This transformation which is done via mathematical relations should (Wowk, 2000) have the ability to show any point relevant to the signal one by one and eliminate irrelevant data. In this regard, varied mathematical methods with different potentials and shortcomings are used. These method could be categorized into two main group: classic signal processing (McFadden and Smith, 1984) and intelligent systems for example FFT, Wigner-Ville distribution (Baydar and Ball, 2001), wavelet (Newland, 1994; Wang and Gao, 2003), Hilbert-Huang transform (Peng and Chu, 2004), blind source separation (Tse *et al*., 2006), statistical signal analysis (Jardine *et al*., 2006) and their combinations (Fan and Zuo, 2006; Farina *et al*., 2008) are classic signal processing methods. ANN-based (Paya *et al*., 1997), GA-based (Samanta, 2004), expert systems (Ebersbach and Peng, 2008), combined algorithms (Rafiee and Tse, 2009; Rafiee *et al*., 2007, 2009) and EMD (Yang and Tavner, 2009) could be classified as intelligent systems. Currently, industrial applications of intelligent monitoring systems have been increased by the progress of intelligent systems. In recent years, many researchers have used EMD methods due to the inefficiency of the aforementioned methods in precise and on time diagnosis of some faults and also the effects of gear faults on vibration frequencies and so making local changes and making the signals unstable. In this respect, Parey activities (Parey *et al*., 2006) were done in gear modeling in order to identify faults at the initial stages of

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the growth via EMD method. Loutridis was the first person who used EMD method in gearbox fault diagnosis with varied cracks in the gear. However, he failed at making an intelligent system (Loutridis, 2004). Yang and Tavner (2009) investigated shaft vibration signals via EMD method (Yang and Tavner, 2009). Lei *et al*. (2009), used a method known as optimized EMD for fault diagnosis; a method which was complex and consisted of more computations compared with EMD method (Lei *et al*., 2009).The main problem in EMD method is its complexity and so needing much experience and insight in physics issues in diagnosing faults. Thus, one of the major challenges in EMD method is having systematic intelligence for intelligent fault diagnosis. In order to solve this problem, Ricci and Pennacchi (2011) aimed at making intelligent choices of optimized Intrinsic Mode Functions (IMFs) for fault diagnosis but their method was restricted to certain faults and lacked a thorough intelligent method for fault diagnosis. So, this project aims at creating an intelligent neural network based on EMD method.

DATA RECORDING

In this study, in order to collect experimental data, a four-speed motorcycle gearbox, a single phase electric motor with 380 w power and nominal speed of 1420 RPM, a multichannel pulse analyzer system, a triaxial accelerometer, an optical tachometer and a coupling for connecting the internal and external shaft of the gearbox and four rubber shock absorber under the system for hindering sudden vibrations are used (Fig. 1).

To have faults on the gears, a 29 teeth gear in the fourth gear is used on the internal shaft. In contact, this gear has the highest circular speed (Fig. 2).

In Fig. 2, A and B indicate the shaft A and shaft B. Gears A4 and B4 are a pair of driving and driven gears. Gears A2 and A4 mounted on the output shaft and B1 and B3 mounted on the input shaft were fixed in the gearbox and N indicates the number of teeth.

Figure 3 shows the faults of slight-worn, broken teeth of the gear and accelerometer location.

Moreover, Fig. 4 and 5 show the vibration signal in the gear with slight worn and medium worn, respectively. The vertical axis shows just relative displacement and has no defined unit.

Figure 6 and 7 indicate the FFT analysis of these faults. As shown, faults cannot be diagnosed via Fig. 6 and 7. In these two diagrams the vertical axis also shows the relative numbers.

Fig. 1: Data recording

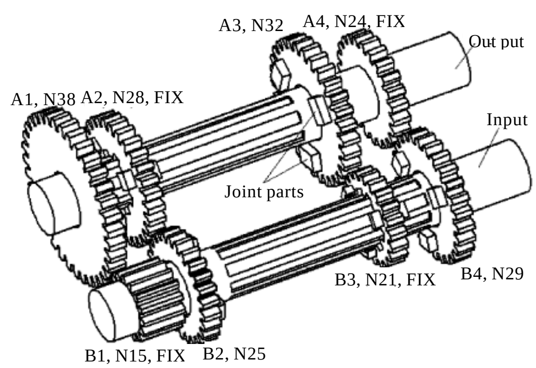

Fig. 2: Schematic diagram of the gearbox

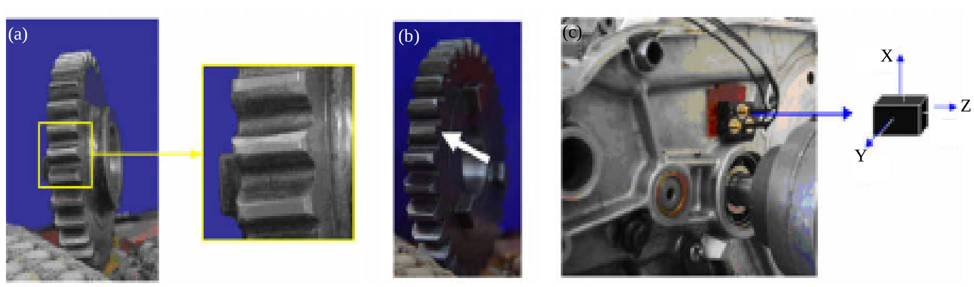

Fig. 3(a-c): (a) Slight worn gear, (b) Broken teeth and (c) Accelerometer location

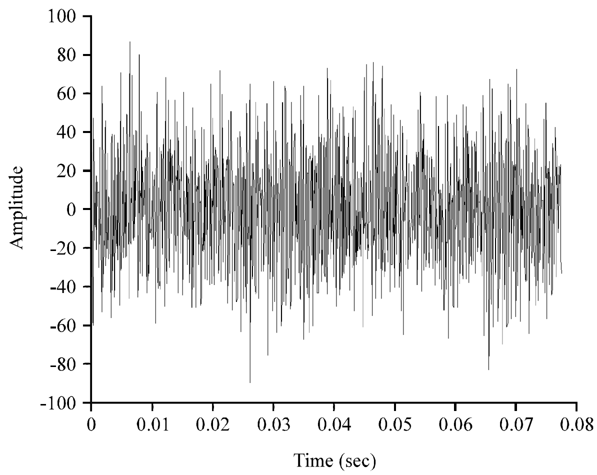

Fig. 4: The slight-worn vibrational signal

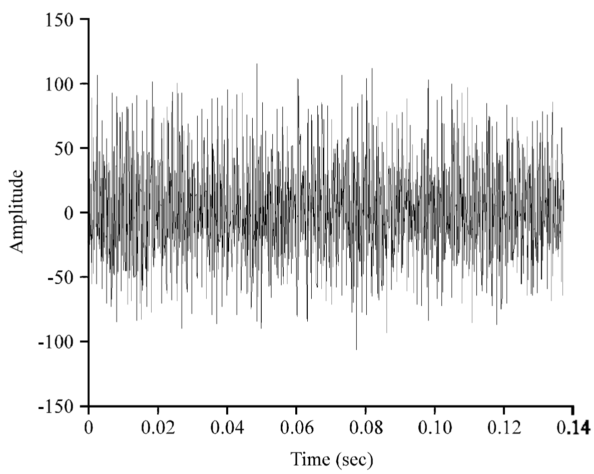

Fig. 5: The medium-worn vibrational signal

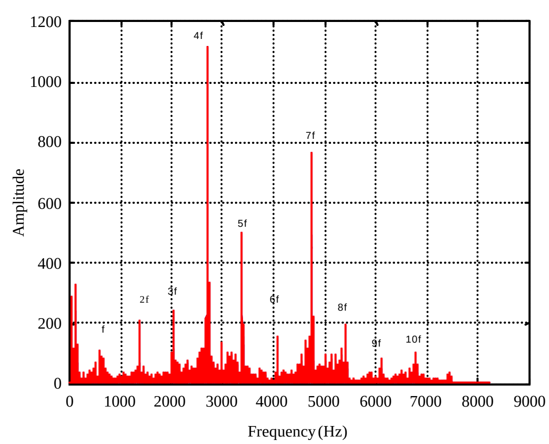

Fig. 6: The slight-worn FFT diagram

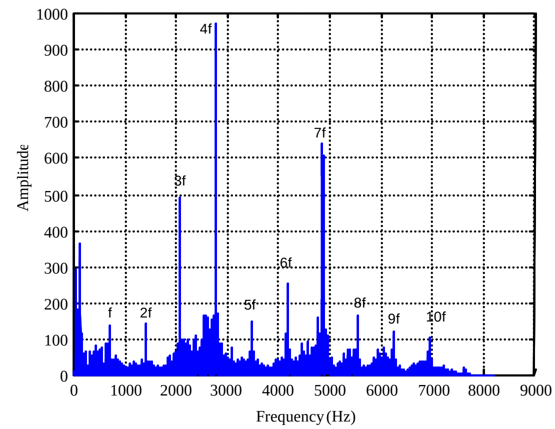

Fig. 7: The medium-worn FFT diagram

EMD METHOD

In EMD method, it is hypothesized that each signal consists of varied simple sine curves (2). Therefore, each signal can be decomposed into a few waves or so called IMFs. In order to have IMFs, the following stages should be done (Yang and Tavner, 2009):

- Identifying all the maximum and minimum local points of the signal
- All maximum points should be linked together via a grade 3 spline. The same should be done for all minimum points
- After computing the average size of maximum and minimum spline, it is defined as m_1 and its difference with the quantity of the main input signal relevant to vibrations (x (t)) is called h_1:

$$x(t)-m_1 = h_1 \tag{1}$$

where, h_1 is the first element to be investigated with regard to whether it is IMF or not? For this reason, two terms should be checked (Huang *et al*., 1998; Loutridis, 2004):

- In all data, the number of zeros and extrema of the signals should at most differ by one number
- The average size of local range of the maximum and minimum in each part of the signal should be the same

If h_1 is not part of IMFs, h_1 behaves as a basic signal and the aforesaid stages should be done again. These stages repeat until h_1 becomes an IMF. The first part of IMF which can be obtained from the data separates from the base signal and the remaining signal acts as a base signal.

HILBERT TRANSFORM ALGORITHM

Each IMF consists of a wave with a certain frequency range. The first IMF is a wave having the highest frequency available in the primary signal. Other IMFs consist of waves with the lowest frequency in the primary signal (Parey *et al*., 2006). The main objective of Hilbert transform of signal C_j (t) is described as follows (Loutridis, 2004):

$$H[C_j(t)] = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{C_j(t)}{t-t_0}\,dt \tag{2}$$

After Hilbert transform, the frequencies in each IMF can be obtained via relations Eq. 3:

$$Z_i(t) = C_i(t) + JH[C_i(t)] = a_i(t)e^{j\theta_i(t)} \tag{3}$$

and

$$a_i(t) = \sqrt{C_i^2(t) + H\,[C_i(t)]2} \tag{4}$$

In the presence of fault frequency in each IMF, the fault can be detected. The diagram of the six first IMFs gained of an average fault signal is shown in Fig. 8. In this Fig. 8 also the vertical axis shows the relative displacement.

CREATING A NEURAL NETWORK

Neural networks which are mainly derived from the human nervous system have been widely used as a kind of intelligent system in recent decades. Learning potential, flexibility and interoperability are features which make neural networks appropriate for scientific and engineering problems.

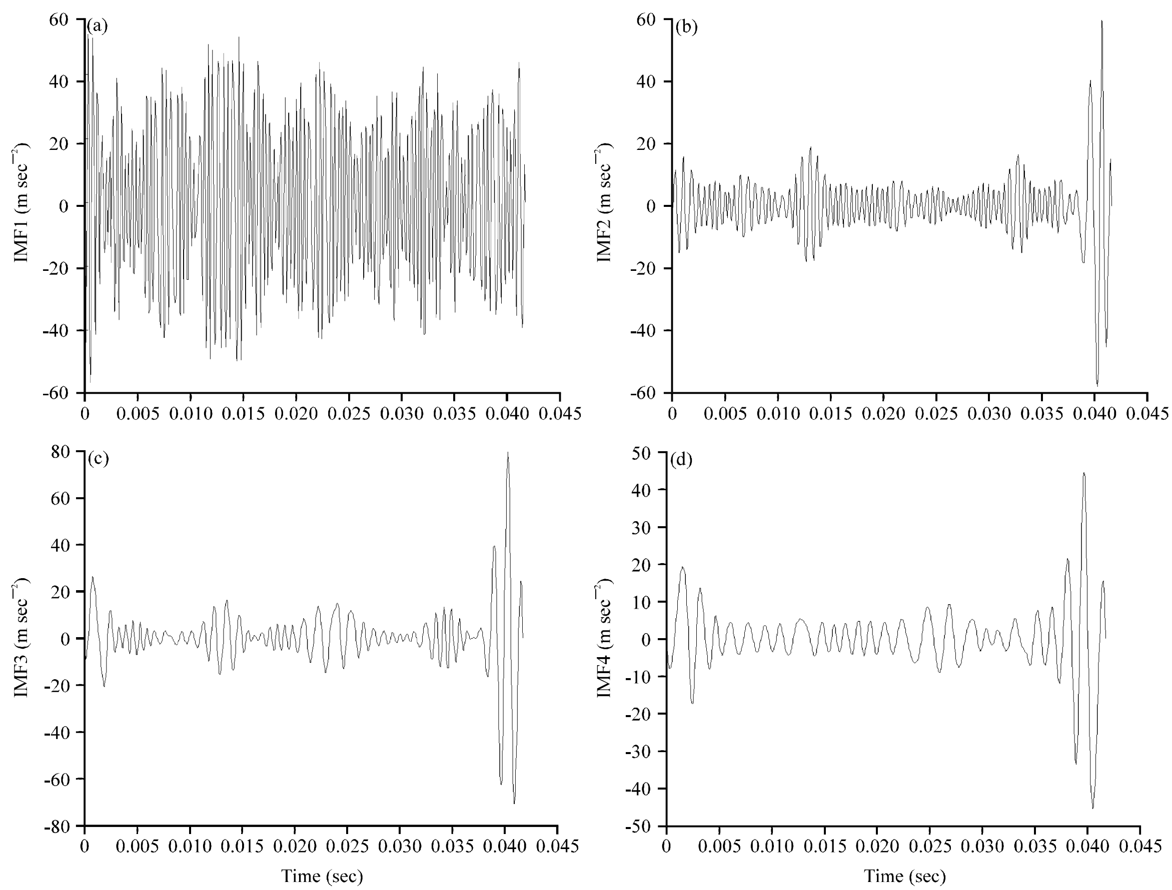

Fig. 8: Continue

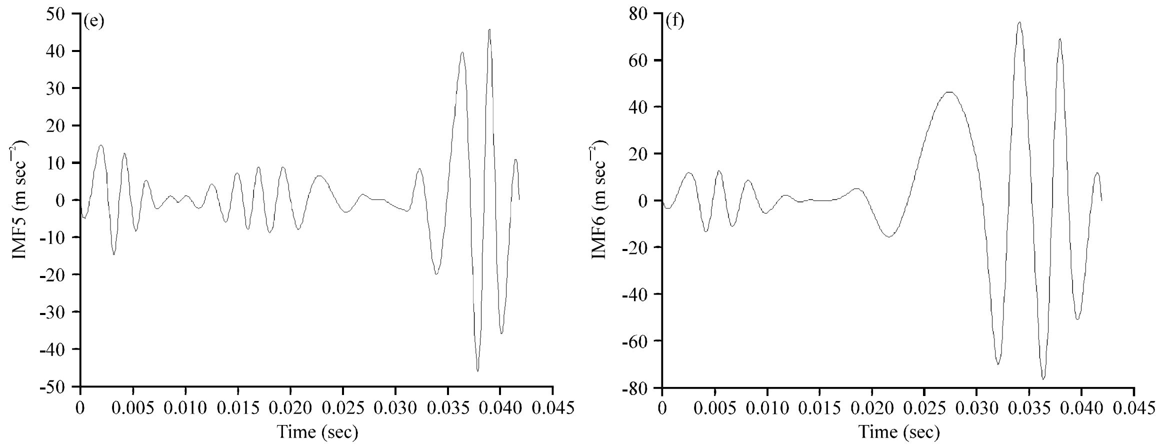

Fig. 8(a-f): The six first IMFs of medium-worn signal, (a) The first IMFs of medium-worn signal, (b) The second IMFs of medium-worn signal, (c) The third IMFs of medium-worn signal, (d) The forth IMFs of medium-worn signal, (e) The first fifth of medium-worn signal and (f) The first sixth of medium-worn signal

Table 1: Comparing the standard deviation (SD) and the root mean square (RMS)

SD of the first six intrinsic mode functions (IFMs)				RMS of the first six intrinsic mode functions (IFMs)			
Faultless	Slight-worn	Medium-worn	Broken-tooth	Faultless	Slight-worn	Medium-worn	Broken-tooth
42.9096	21.0224	24.3843	33.9922	38.2577	22.4913	26.1987	39.4564
18.7598	14.1941	20.7309	34.6533	15.6148	17.2084	21.3528	31.4283
7.9966	6.8833	7.2478	10.8018	7.0608	6.3387	6.8745	9.8407
8.6987	4.4158	5.929	8.415	4.7397	4.6425	4.3063	5.928
8.9609	5.0545	7.352	8.2265	6.0275	4.9656	2.9353	7.3935
9.7403	15.0638	6.3042	5.6479	9.1176	4.9925	2.7754	4.8117

Table 2: The results of testing the neural network via standard deviation (SD) and the root-mean-square (RMS)

Validation of SD results					Validation of RMS results				
Net structure	Faultless (%)	Broken-tooth (%)	Medium-worn (%)	Slight-worn (%)	Net structure	Faultless (%)	Broken-tooth (%)	Medium-worn (%)	Slight-worn (%)
6:10:4	100	100	100	100	6:11:4	100	100	100	100
6:11:4	100	100	100	100	6:12:4	100	100	100	100

To diagnose faults, in this study first each signal is decomposed into several sub-signals via EMD method in the MATLAB programming software. Then, standard deviation and the root mean square of the first six signals are computed (Table 1) at different stages and used as the input of the neural network in different networks. Therefore, the toolbox of the neural network in the MATLAB software is used. The network used has a two-layered perception structure with error back propagation as its learning algorithm and Sigmoid function as transfer function for all layers.

The data collected from 100 revolutions of vibration signal in each group of gearbox fault was used to teach the network. Then, in order to investigate the performance of the network in each fault, 100 vibration signals are tested. Table 2 shows the results of testing the neural network via standard deviation and the root-mean-square, respectively.

CONCLUSION

In this study, a neural network is offered for fault diagnosis via EMD method which has less input compared with wavelet analysis method. Besides, the method suggested in this study is more accurate and provides precise answers in all cases. Thus, both suggested methods (computing standard deviation and root-mean-square) not only are accurate enough but also have reduced the size of computations to a great extent.

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